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An activity-based integrated land-use transport model for urban spatial distribution simulation

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Abstract

This research develops an activity-based integrated land use/transport interaction model based on the concepts – activities (mainly, households and employment activities), activity location and relocation for Chinese regions. It consists of a residential and employment location sub-model, a transport sub-model and an implicit real estate rent adjustment sub-model. The model is developed to model the urban activity distribution evolution, predict urban spatial development trends and examine various planning decision implications. It spatially distributes household and employment activity change of a study area by zone based on the current activity distribution, land use policies and the accessibilities of the zones. The model is subsequently calibrated to predict the distribution of households and employment activities in Beijing metropolitan area in 2025. Model results show that the resident and employment densities are still high in central Beijing in 2025, and most zones' resident densities are higher than their employment densities. However, there is also significant population density increase along the 6th ring road, indicating the relocation trend of the residents and businesses to the outskirts. This is consistent with the government objectives to decentralize activities within the central urban area. The paper also suggests that the model should be used mainly in examining the possible differences arising from the adoption of different policies though predicting future of a city distribution proves feasible.

Keywords

Accessibility, urbanization, location, relocation

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Introduction

China's rapid urbanization has generated a number of mega cities including the capital Beijing and also caused massive urban issues (Gu and Pang, 2009; Li et al., 2012; Liu et al., 2012; Lu et al., 2007). As Beijing is over-burdened in the Beijing-Hebei-Tianjin region, Chinese government intends to redistribute its households and business activities to suburban areas. However, the reconstruction of an urban spatial structure should be based on the complete understanding of the relationships among these activities within the urban system, at present most researchers only concentrate on some parts of the urban system such as residential location and commuting (Chai et al., 2011; Dang et al., 2011; Dong et al., 2011; Lu et al., 2007; Liu et al., 2010; Shen and Chai, 2012; Zhao et al., 2013), physical land use change (Li and Liu, 2007; Long et al., 2009; Zhou and Ye, 2013), industrial space and urban form (Chu and Liang, 2007; Gu et al., 2013; Yang and Li, 2009; Zhang and Chen, 2011), transport and urban form (Chen et al., 2010; Dai and Li, 2009), etc. Attempts to model urban spatial evolution in terms of urban land use-transport integration based on activates are rare.

Urban spatial structure evolution can be described by the spatial change of urban socio-economic activities such as households and business activities. Activity location and relocation is one major factor determining population travel while transport also shapes the distribution of these activities and urban land use. On the other hand, the land use and transport systems are closely related, and in practice there is an increasing need to integrate them for sustainable urban development planning (Brandi et al., 2014). Urban Land Use/Transport Interaction model (LUTI) is traditionally used to model the interaction (Coppola et al., 2013; Simmonds and Feldman, 2011; Torrens, 2000; Wegener, 2004) for possible effects of new policies or operation principles of the existing urban systems (Aljoufie, 2014; Echenique et al., 2012; Foot, 1981; Lowry, 1964; Wegener, 2004; Zondag et al., 2015). Notwithstanding the usefulness, the LUTI models for cities only thrill in developed countries, with rare application for developing countries, especially China.

Batty (2013, 2008) classifies the LUTI models into two traditions: models with various theoretical dynamics associated with equilibrium approaches such as Lowry (1964) types and models more physically based land-development models mirrored around cellular automata and agent-based models. Agent-based modeling requires comprehensive data at microscopic level to show the distinction, complexity and decision making of each individual, while the Lowry type LUTI models usually uses aggregated datasets. The complexity of characterizing agent behaviors (e.g. companies with different sizes have different market behaviors) is also a big hurdle for researchers. Moreover, agents usually evolve stochastically which often leads to varied results subject to subjective interpretation. Unfortunately, traditional Lowry type models also have their weaknesses. They are not suitable for modeling behavioral response to many travel demand management policies (Wegener, 2004), are restricted to population and service sectors and produce results at a single time point only.

General spatial distribution changes are essentially influenced by household and economic activities (Lowry, 1964; Simmonds and Feldman, 2011; Wegener, 2004). These activities are capable of illustrating different processes of these changes which in turn affect activities and the spaces they occupy. Unfortunately a land use/transport interaction model based on activities is never clearly put forth and implemented in practice (Aljoufie, 2014; Batty, 2008; Batty et al., 2013; Chen et al., 2010; Coppola et al., 2013; Gu et al., 2013; Lowry, 1964; Simmonds and Feldman, 2011; Wegener, 2004; Zhao et al., 2013; Zhou and Ye, 2013; Zondag et al., 2015). In the face of the need in China, this study is intended to develop an activity-based LUTI model as a decision support tool, e.g. to check implications of various planning decisions including zone development and transport investment choices. The paper defines activity-based model as an altered Lowry type LUTI model used to simulate the evolution of urban spatial distribution with time states based on activities (e.g. households and business activities) using space (commonly, floorspace), and aggregate macroscopic datasets. In the paper, land-use is referred as the social and economic activities using space on the land, e.g. floorspace, rather than the land itself. Activity location and relocation and transport are key factors to be modeled as they determine population travel therefore shape the distribution of activities and urban land use. Only a proportion of total activities will be relocated in a time period in the model, which retains the existing process of a city and in the meantime is able to model the demographic and economic interaction by the additional process of migration and regional economic change.

The paper is organized as follows. Sections "Integrated model architecture" and "Model components" provide a detailed description of the proposed activity-based LUTI model and its components. Section "An application – Beijing metropolitan area" applies the model to Beijing to forecast Beijing urban activity distribution in 2025 by type. Sections "Discussion and future work" and "Conclusions" conclude with the next stages development of the model.

Integrated model architecture

The model consists of a residential and employment activity location sub-model, a transport sub-model and an implicit real estate rent adjustment sub-model. Its flow diagram is shown in Figure 1. The household activities and business activities are represented by housing and employment, respectively.

According to the utility theory that individuals choose locations to maximize their overall utility or profit, the location model assumes that workers and employers make location choices based on zonal characters such as accessibility and real estate rent. This is implemented by applying probabilistic discrete choice approach (Coppola et al, 2013; Hsu and Guo, 2006; Train, 1986) as shown later, where the probability that an individual chooses a discrete location depends on the aggregate choice of other individuals. Moreover, the model assumes zonal characters such as transport accessibility and rent change cause the distribution variation of urban activities such as household location or relocation. Generally only a minor proportion of urban activities, namely, mobile activities, choose to relocate every year. This is set exogenously currently in the model.

As Figure 1 shows, the location model spatially distributes residents and employment into zones of a city. The activity distribution along with land use policies and transport determines the accessibility of each zone and then the location of the activities. The change in activity distribution causes the change of activity density or rent, and then the accessibilities of these zones are rebalanced. The process is repeated until the stopping criterion is met, that is, the activity distribution difference between two successive iterations is below a predefined value. The model outputs the forecast results for the period p, which is then taken with floorspace development scenario as the input for next period *p+1*. The employment location model shares the similar process as the residential location model.

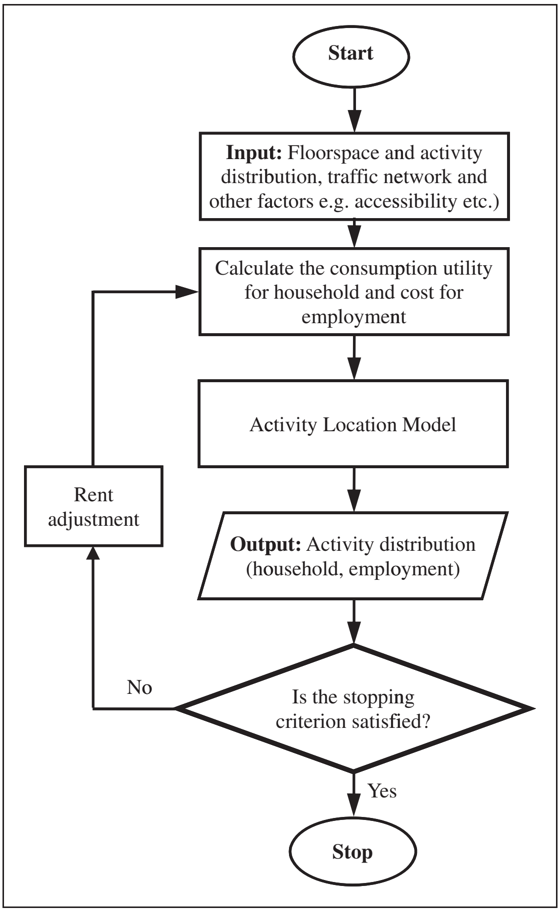

Figure 1. The activity-based LUTI model flow diagram.

Model components

Transport accessibility

The transport accessibility of each zone in a city is indicative of the zone's attractiveness and is estimated from the distribution of opportunities and transport cost to the zone. A city affords metro lines and roads of different classes from motorways to minor roads intersecting with each other to form a transport network. Transport cost between zones is estimated based on the time cost and economic cost determined by distance and road types.

The accessibility is defined as the ease that the transport system allows one to get to a bundle of opportunities such as workplaces from a particular zone, calculated for each activity. For households, the model calculates Origin Accessibility (OA) which indicates how easy (or difficult) it is for residents to travel from a residential zone to opportunities. For business, the model calculates Destination Accessibility (DA) indicating the accessibility of an employment location for residents in the city. Given that households usually involve different groups such as elder, working class and children, the model also weights the accessibilities of hospital, employment and school locations. Moreover, the model assumes that the businesses seek locations more accessible to residents in DA calculation.

Two key drivers of the zonal accessibility are considered, i.e. the transport cost between zones and the opportunity distribution. In contrast to traditional methods of calculating transport accessibility (Wang et al., 2015; Zondag et al., 2015), the model uses a logsum formula associated with a logit model of destination/origin choice as follows,

$$A_i^n = \frac{1}{-\lambda} \ln\left\{ \sum_j W_j \exp\left(-\lambda \cdot g_{ij}\right) \right\} \tag{1}$$

where

A_i^n	is the accessibility of activity type n for zone i;
j	refers to a zone whose connection with i is under consideration;
g_{ij}	is the transport cost of transport from zone i to zone j;
W_j	represents the importance of the connection for A_i;
λ	is the coefficient of traffic cost.

W_j measures the medical service, educational service and employment opportunities afforded by zone j for OA, and the number of residents in zone j for DA. Negative λ realizes the traffic cost and therefore the exponential term discounts W_j.

Consumption utility

Statistic shows that households spend their more than one third income on housing (Eurostat, 2014; Sohu, 2016; USDA, 2014). In the simplest case, the research defines the utility of consumption as the household satisfaction obtained from their income spent on two goods, namely, housing space and *ogs* (i.e. other goods and services) based on Cobb–Douglas function,

$$U_{pi} = \left(a_{pi}^H\right)^{\beta_p^H} \cdot \left(a_{pi}^O\right)^{\beta_p^O} \tag{2}$$

$$\beta_p^H + \beta_p^O = 1 \tag{3}$$

where U_{pi} is the household utility during period p in zone i, a_{pi}^H is the average housing space occupied by a household, a^O is the average expenditure on *ogs*, and β_p^H and β_p^O are the propensities to spend the income on housing space and *ogs*, respectively. Transportation cost takes the second largest share of household expenditure, but is excluded here as it is counted implicitly in the following location utility equations.

Activity location choice

Residential location choice. The residential location model forecasts the number of households by zone. It assumes that individuals choose locations to maximize utility with constraints of floorspace distribution and locations where households previously located. The factors that affect residential location including OA and a set of real estate rents are weighted to the location utility (V). The consumers for housing spaces value zones as a function of their environmental and locational attributes relative to the work place. As how individuals value different locations is unknown, a probabilistic discrete choice model (Coppola et al., 2013; Hsu and Guo, 2006; Train, 1986) is used to estimate the probability that residents choose zone i as their place of residence, in which the error terms are assumed to be independently and identically distributed (Coppola et al., 2013; Gumbel, 1941). Therefore, the probability that residents choose zone i as their place of residence is given here as,

$$H(L)_{t+1,i} = H(M)_{t+1} \cdot \frac{H_{ti} \cdot \left(\frac{F(A)^{H}_{t+1,i}}{F(A)^{H}_{ti}}\right) \cdot exp(\Delta\ V^{H}_{t+1,i})}{\sum_{i} H_{ti} \cdot \left(\frac{F(A)^{H}_{t+1,i}}{F(A)^{H}_{ti}}\right) \cdot exp(\Delta\ V^{H}_{t+1,i})} \tag{4}$$

where $H(L)_{t+1,i}$ is the number of households moving to the zone i during the time $t+1$ and $H(M)_{t+1}$ is the total number of households to locate in the city, while H_{ti} is the total households in zone i at time t. $F(A)_{ti}$ is the housing floorspace occupied in zone i at t by mobile households, $F(A)_{t+1,i}$ is the total housing floorspace available from the land use policy scenario at $t+1$, which includes the available floorspace left at t plus the incremental floorspace at $t+1$ in zone i. $\Delta V_{t+1,i}$ is the utility weighted as the sum of the accessibility change and consumption utility change, while the consumption utility is estimated based on average wage and real estate rent.

Employment location choice. The employment here refers to the economic activities excluding households. The employment location model determining the employment distribution by zone is similar to the household location model above, by only replacing household terms with the ones relating to employment. It estimates the location of mobile activities including the migrants and relocating local residents, which generally accounts for a small percentage of the total. The model assumes that the location of each mobile employment is affected by the location of the population.

Real estate rent

@@The distribution (i.e. densities) change of the household and business activities due to the location of these activities as shown in the location model above subsequently causes the change of zonal rent. The real estate rent model then re-estimates the rent by zone and again re-calculates the location of these activities. It calculates the average property rents for each zone as a function of supply and demand and the previous rent levels. The rent is the major factor affecting the utility/profitability of activities. The rent changes in accordance with the multiplication of demand relative to the supply of floorspace. For housing, the rent is estimated as,

$$r'^{H}_{pi} = r^{H}_{pi} \cdot \left[\frac{\sum_{h} a^{H}_{pi} \cdot \left(H(L)^{h}_{pi}\right)}{F(A)^{H}_{pi}}\right] \tag{5}$$

where r' is the newly estimated rent of housing floorspace in zone i, while r at the right of the equation is the previous rent. Variable a is the present density of household activities. $H(L)^{h}$ is the quantity of households of type h in zone i. $F(A)_{p}$ is the current quantity of available floorspace. In the same way the rent equation for employment floorspace is obtained by substituting the household variables and parameters for employment ones.

An application – Beijing metropolitan area

Study area introduction and data

There were 18 districts, i.e. counties in Beijing (later adjusted to 16 districts), 14 of which are inside or intersect with the 6th Ring Road – the outmost ring road. The other four remote suburban districts, i.e. *Huairou, Miyun, Pinggu, Yanqing* are outside the ring road. The 14 districts are modeled at town levels with four remote districts at district level. They are disaggregated into 243 zones including districts (also, called counties by administration) and towns as shown in Figure 2.

The 6th Chinese Census data (NBSC, 2012) provides zonal demographic data relating to households, workers, the elderly and children. The subsequent years are extrapolated linearly in the model based on the average annual population growth and population estimates. The employment activity data with detailed employment distribution of Beijing is prepared based on Baidu Map Point of Interest data (Baidu, 2013) and Beijing Economic Statistics Yearbook (CSP, 2013), which covers companies, organizations, institutes and hospitals etc., with more than 700,000 records. The data information by company includes the scale, location, fixed assets and employees etc.

The spatial data includes the administrative divisions at county and town levels and road networks with roads at various levels such as highways, urban express roads, national roads, provincial roads and county roads. The GIS technique is applied to deal with the intersection of metro lines and roads. If a road intersects with the buffer area of a metro station, the road and the metro line are considered to intersect with each other. A transport cost matrix for all pairs of zones is calculated based on the estimated average speed for the roads at the various levels.

In the model the urban activities are classified into two broad types: household or housing and business or employment activities. The household data describes the distribution of households and population at workers, elder citizen and children level by town. The employment data is used to generate the distribution of all jobs.

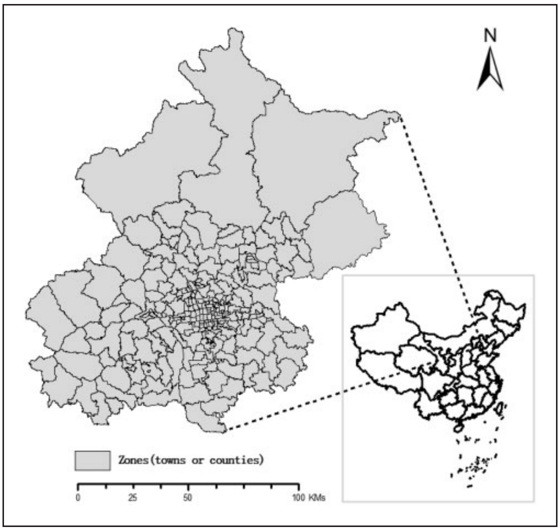

Figure 2. Study Area: Beijing, China.

Model calibration and goodness-of-fit of the model

The model applies an automated calibration procedure to the specified coefficients. It starts from a predefined date and a known state with the best guess of a value set, and then compares the results with the observed values on a defined end date. In practice the predicted rent values by zone are used in the comparison. If they differ significantly from the corresponding observed values, the coefficients are adjusted based on the hill climbing algorithm. More specifically, if the rents are greater than the observed values while the correlation between them is less than a threshold, say, 0.60, the coefficients are reduced or increased by proportion according to the sign of the correlation. This procedure continues until it converges against the observed data.

Activity distributions are predicted from based year 2010 on a yearly basis. As lack of census data for the following years, the endogenous rents are used and validated against the observed rents in 2014 (Sofang, 2014). The results between the two show a satisfactory correlation, R^2=0.8. Data quality safeguarded by appropriate data pre-processing methods directed by economic theories also plays an important part for a good model fit. The model uses the factor, affordability, from the housing demand models (Albouy and Ehrlich, 2014; Mumtaz, 1995) as the determining factor of the rent. It states that the rent positively correlates with the income level of households. In the model the observed rents are determined by total household income over floorspace. More specifically, they are calculated as the household expenditure on the unit of floorspace based on the household income level, adjusted by a ratio factor, i.e. the total household expenditure on floorspace over the total floorspace value. The estimated rents in the model could oscillate out of the range and will not converge, so the outliers of the observed rents are dropped before the modeling process starts.

Results

Scenario: land use development. The model calculates the distribution of business in terms of employment. The corresponding land use represented by floorspace is categorized into housing and employment floorspaces.

The government sells land use rights to developers on a yearly basis in Beijing with the usage types either housing or employment and the permissible amount of floorspace that could be developed on it. The research collects the latest land transactions data by zone from 2009 to 2013 and averages them to provide a starting point for the designation of future land use policies for each year as shown in Figure 3. The maps indicate that the employment floorspace development intensity on the outskirts of Beijing is much greater than the housing floor space development, implying that the employment activities are locating or relocating to the outskirts. Here the population and employment growth rates are set equal exogenously.

2025 forecast activity distribution. The land use scenario above is then applied to the model and the urban development trends in Beijing up to 2025 are forecast. The residential and employment distributions in 2025 are shown in Figure 4(a) and (b). The results are then compared with the activity distributions in 2010 in Figure 4(c) and (d).

According to Figure 4(a) and (b), the residents and employment densities are still high in central Beijing in 2025, with most zones whose residents' densities are more concentrated than the employment and only few zones showing high employment densities. Figure 4(c) and (d) shows the differences between the years 2025 and 2010 residential population and employment distributions respectively. As shown in Figure 4(c), the population density of each zone has increased along with the total population increases, though the higher

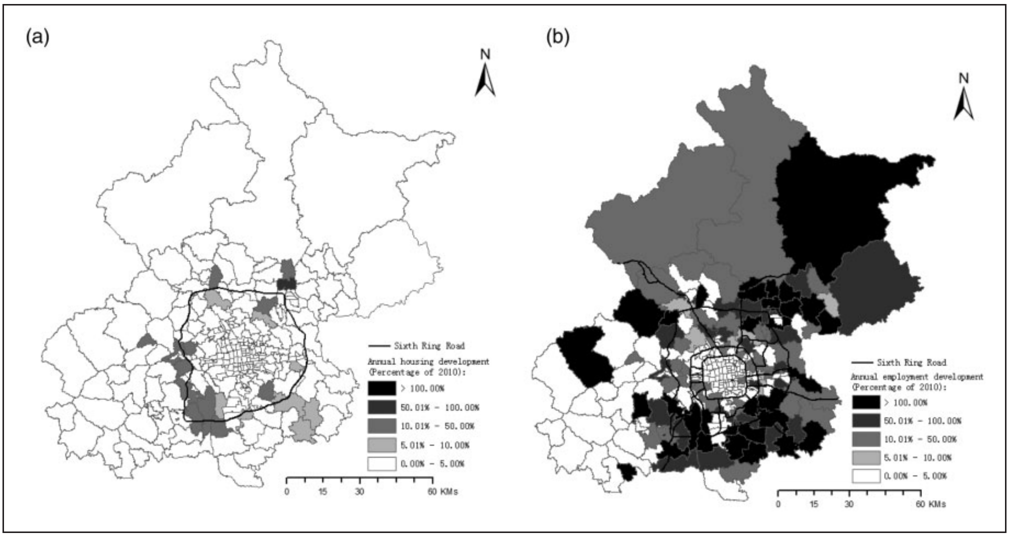

Figure 3. Trend of floorspace development. (a) Housing. (b) Employment.

population density increase is mainly located along the 6th ring road. The employment distribution change is more decentralized from Figure 4(d). Some zones' (mainly, in central city) employment densities decrease, even though the overall employment increases by 2% as set in the scenario. This indicates that with more floorspace developed in suburb, more businesses will move from the central urban areas with higher rents to outside of the city for lower rents, while the residents still prefer to live close to the central city because of the high transport accessibility and jobs. Nevertheless, the growth patterns in Figure 4(c) and (d) indicate the trend that more and more people and jobs are moving to the outskirts.

Discussion and future work

Usefulness of the model

This study is intended to provide a methodology or tool to test the urban land use or transport policies. In this study, an automatic calibration method is implemented. Though the results of goodness-of-fit tests are encouraging, modeling the future development of cities remains difficult, as unexpected factors affect location rents and the behavior of actors can change. The model perhaps should not be used to predict the future distribution of a city but as a tool for examining the possible differences arising from the adoption of different policies in a context of a continuation of past behavior of actors.

Land use policies

The land market modeling nonetheless remains important as the land market is a key factor affecting the floorspace development. As suggested in the paper, the aim of this study is to provide a tool to test land use/transport policy scenarios and project various activity distributions. However, at present this model does not have a land use market sub-model.

The decentralization of the urban activities in Beijing is currently being planned by the authority as a consequence of the heavy traffic congestion and pollution in the central city. For example, a new airport will be built in the south of Beijing; the municipal government is

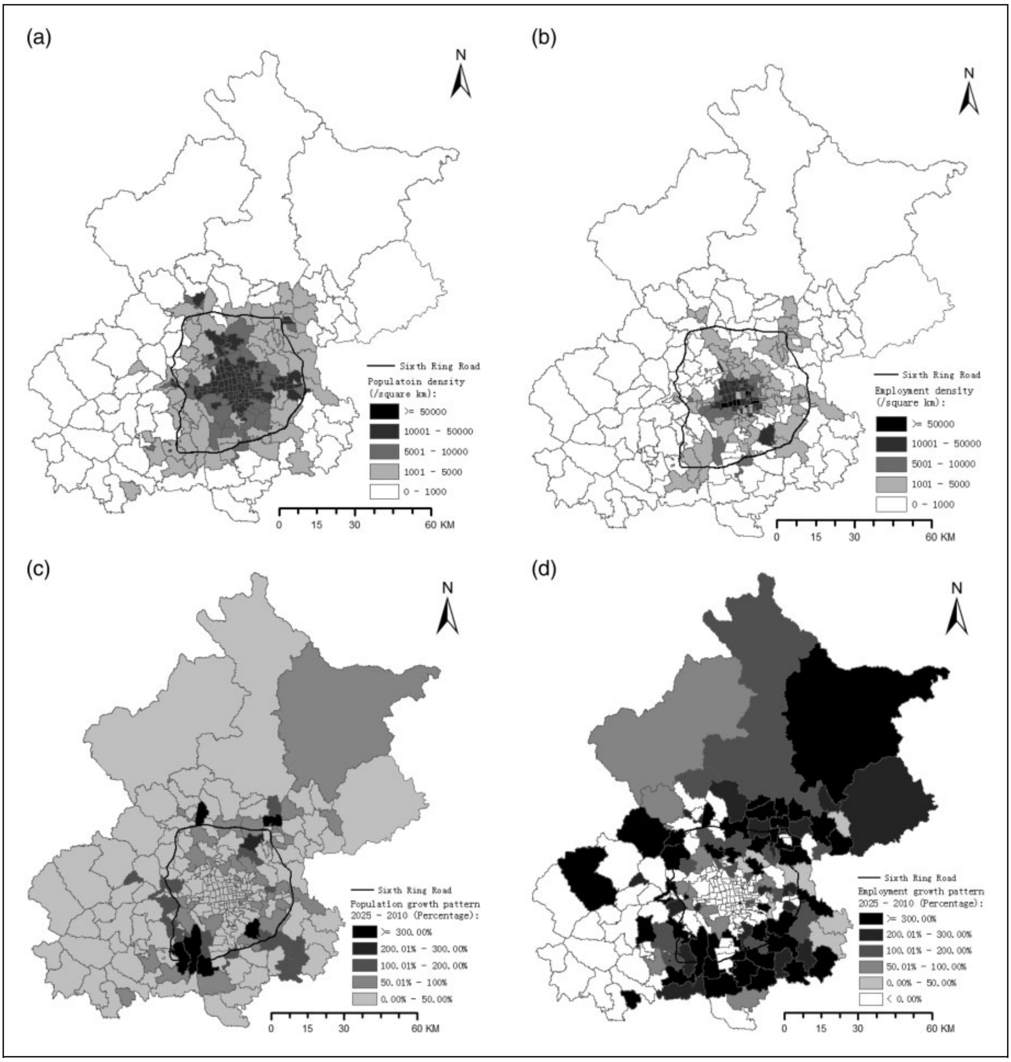

Figure 4. Resident and employment growth patterns (2025 vs 2010). (a) 2025 Residential distribution. (b) 2025 Employment distribution. (c) Population growth pattern. (d) Employment growth pattern.

considering the move to the suburban district of *Tongzhou*. These further stimulate the floorspace development on the outskirts of the city. Even so, as these projects will not be realized for a number of years, this study assumes that the current land use policy trends will continue. In practice these trends may not necessarily be the real future policies of the authority.

Beijing's urban land use and floorspace development is partly determined by the government and developers and further influenced by the land market. As the floorspace is one of the key factors determining the urban activity distribution, a sub-model to forecast the floorspace development pattern with respect to the land market requirements needs to be developed.

Location utility and modeling spatial scale

In this study, the location utility/profitability is estimated as the weighted sum of its accessibility affected by transport cost and activity distribution and its consumption utility/profitability measured by rent.

The model is applied to Beijing at zone or so-called town scale. It is the most detailed and finest scale at which a model has ever been constructed in China. A town however is still a considerably large area with varied employment activities.

Implementation of the model at an even lower level such as a neighborhood or community level is possible but requires an efficient algorithm with more detailed data and high performance computing. An alternative method is to work with other models toward an integrated solution.

Activity categorization and accessibility estimation

This study differentiates the accessibility by activity. Based on the family member age, the household accessibility is divided into three parts, i.e. the hospital accessibility for the elderly, the workplace accessibility for workers and the school accessibility for children. The employment accessibility is estimated at sectoral level. However, different companies may have different degrees of sensitivity to the distribution of the residential population and needs for space to access to the utilities and suppliers. With the data available it is feasible to develop a model to estimate the employment accessibility at company level.

The households are currently treated as a single socio-economic group in the model. However, households can be classified into groups based on the income level and preference of transport. Perhaps, one of the targets for the next version of the model is to develop a more sophisticated household accessibility estimation sub-model by identifying different socio-economic groups.

Transport scenario

This study does not incorporate any change in the transport system as it usually alters more slowly than the land use. However, the model is capable of modeling the impact of the transport system change on the activity distribution. For example, the transport cost can be re-estimated with an updated road network. The transport accessibility and transport cost variables provide strong functionalities for transport policy simulation and an interface to integrate with other intelligent transport tools.

Conclusions

This research enriches the land use/transport interaction model portfolio by developing an activity-based LUTI model using the concepts – activities (mainly, households and employment activities) and activity location and relocation. The model is predominately a tool for a region to test its land-use and transport policies. It is an equilibrium model, comprising a residential and employment activity location sub-model, a transport sub-model and an implicit real estate rent adjustment sub-model. The urban activity location and relocation is determined iteratively. The model is subsequently applied to Beijing to forecast the distribution of activities in 2025 based on the present land use policies. Modeling results show that the zones in central city have higher population in 2025 than that in 2010, but with the decreasing number of employment. The results also indicate that more residents and employers choose to locate on the outskirts of the city.

The results provide evidence that the model is capable of quantifying the activity distribution change by zone and supporting decision makers to test new urban land use and transport policies. The model can be applied to other cities in China with refinement. The study is the first step in developing LUTI type models to examine the urban spatial evolution and support the sustainable development of Chinese cities within a large work program. As discussed, a set of sub-models will be developed in the next generation of the model. Other further work includes model validation based on retrospective methods using historical data, the Other Services (i.e. *ogs*) endogeneity, and the improvement of zone valuation.

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References

Albouy D and Ehrlich G (2014) Housing demand and expenditures: How rising rent levels affect behaviour and costs-of-living over space and time. NBER. Available at: http://cba.unl.edu/academic-programs/departments/economics/about/seminar-series/documents/housingexpenditures.pdf (accessed 14 March 2017).

Aljoufie M (2014) Toward integrated land use and transport planning in fast-growing cities: The case of Jeddah, Saudi Arabia. *Habitat International* 41: 205–215.

Baidu (2013) APIStore. Baidu, Inc. [Online]. Available at: http://apistore.baidu.com/ (accessed 28 July 2016).

Batty M (2008) Fifty years of urban modelling: Macro statics to micro dynamics. In: Albeverio S, Andrey D, Giordano P, et al. (eds) *Dynamics of Complex Urban Systems: An Interdisciplinary Approach*. Heidelberg: Physica, pp. 1–20.

Batty M, Vargas C, Smith D, et al. (2013) SIMULACRA: Fast land-use-transportation models for the rapid assessment of urban futures. *Environment and Planning B* 40: 987–1002.

Brandi A, Gori S, Nigro M, et al. (2014) Development of an integrated transport-land use model for the activities relocation in urban areas. *Transportation Research Procedia* 3: 374–383.

Chai YW, Zhang Y and Liu ZL (2011) Spatial differences of home-work separation and the impacts of housing policy and urban sprawl: Evidence from household survey data in Beijing. *Acta Geographica Sinica* 66(2): 157–166 (in Chinese).

Chen YM, Li SY, Li X, et al. (2010) Simulating compact urban form using cellular automata and multicriteria evaluation: A case study in Dongguan. *Acta Scientiarum Naturalium Universitatis Sunyatseni* 49(6): 110–114.

Chu B and Liang JS (2007) Studies on the location factors' impacts of manufacturing industry in Beijing with ordered probit model. *Geographical Research* 26(4): 723–734 (in Chinese).

Coppola P, Ibeas A, dell Olio L, et al. (2013) LUTI model for the metropolitan area of Santander. *Urban Planning and Development* 139(3): 153–165.

CSP (China Statistical Press) (2013) *Beijing Economic Statistics YearBook*. Beijing: China Statistics Press.

Dai JC and Li X (2009) Multi-agent systems for simulating traffic behaviors. *Chinese Science Bulletin* 54(21): 3380–3389.

Dang YX, Zhang WZ and Wu WJ (2011) Residents housing preferences and consuming behaviors in a transitional economy: New evidence from Beijing, China. *Progress in Geography* 30(10): 1203–1209 (in Chinese).

Dong GP, Zhang WZ, Wu WJ, et al. (2011) Spatial heterogeneity in determinants of residential land price: Simulation and prediction. *Journal of Geographical Sciences* 66(6): 750–760 (in Chinese).

Echenique MH, Hargreaves AJ, Mitchell G, et al. (2012) Growing cities sustainably. *Journal of the American Planning Association* 78(2): 121–137.

Eurostat (2014) *Housing Statistics*. Eurostat – Statistics Explained [Online]. Available at: http://ec.europa.eu/eurostat/statistics-explained/index.php/Housing_statistics (accessed 10 October 2016).

Foot DHS (1981) Operational urban models: An introduction. *New York* 37(3): 285.

Gu C, He D and Yuan XH (2013) Transformation of urban spatial structure under the service economy: A case study of Beijing. *Research of Urban and Regional Planning* 1: 71–95 (in Chinese).

Gu C and Pang H (2009) Evolution of Chinese urbanization spaces: Kernel spatial approach. *Scientia Geographical Sinica* 29(1): 10–14 (in Chinese).

Gumbel EJ (1941) The return period of flood flows. *The Annals of Mathematical Statistics* 12: 163–190.

Hsu CI and Guo SP (2006) CBD oriented commuters' mode and residential location choices in an urban area with surface streets and rail transit lines. *Journal of Urban Planning & Development* 132(4): 235–246.

Li J, Deng XZ and Seto KC (2012) Multi-level modeling of urban expansion and cultivated land conversion for urban hotspot counties in China. *Land Scape and Urban Planning* 108: 131–139.

Li X and Liu XP (2007) Case-based cellular automaton for simulating urban development in a large complex region. *Journal of Geographical Sciences* 62(10): 1097–1109 (in Chinese).

Liu Z, He C, Zhang Q, et al. (2012) Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008. *Land Scape and Urban Planning* 106: 62–72.

Liu XP, Li X, Chen YM, et al. (2010) Agent-based model of residential location. *Journal of Geographical Sciences* 65(6): 695–707 (in Chinese).

Long Y, Han H and Mao Q (2009) Establishing urban growth boundaries using constrained CA. *Journal of Geographical Sciences* 64(8): 999–1008 (in Chinese).

Lowry IS (1964) *A Model of Metropolis Memorandum*. Santa Monica, CA: The Rand Corporation.

Lu D, Yao S, Li G, et al. (2007) Comprehensive analysis of the urbanization process based on China's conditions. *Economic Geography* 27(6): 883–887 (in Chinese).

Mumtaz B (1995) Meeting the demand for housing, a model for establishing affordability parameters. The Bartlett Development Planning Unit. Available at: www.ucl.ac.uk/silva/bartlett/dpu/publications/dpu-paper-73 (accessed 14 March 2017).

National Bureau of Statistics of China (NBSC) (2012) 2010 Population Census [Online] Available at: www.stats.gov.cn/English/statisticaldata/CensusData/ (accessed 10 October 2016).

Shen Y and Chai Y (2012) Study on commuting flexibility of residents based on GPS data: A case study of suburban mega-communities in Beijing. *Journal of Geographical Sciences* 67(6): 733–744 (in Chinese).

Simmonds D and Feldman O (2011) Alternative approaches to spatial modelling. *Research in Transportation Economics* 31: 2–11.

Sofang (2014) The web of properties search (in Chinese) [Online]. Available at: http://bj.sofang.com/ (accessed 10 October 2014).
Sohu (2016) House price to income ratios and ranking of Chinese cities in 2016 (in Chinese). Sohu, Inc. [Online]. Available at: http://mt.sohu.com/20160420/n445162076.shtml (accessed 10 October 2016).
Torrens PM (2000) *How Land-Use Transportation Models Work*. London: Centre for Advanced Spatial Analysis.
Train K (1986) *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. Cambridge: The MIT Press.
USDA (2014) Share of U.S. household consumer expenditure by major categories, 2014. U.S. Bureau of Labor Statistics, Consumer Expenditure Survey, 2014 [Online]. Available at: www.ers.usda.gov/data-products/chart-gallery/detail.aspx?chartId=40040 (accessed 10 October 2016).
Wang Y, Monzon A and Ciommo FD (2015) Assessing the accessibility impact of transport policy by a land-use and transport interaction model – The case of Madrid. *Computers, Environment and Urban Systems* 49: 126–135.
Wegener M (2004) Overview of land-use transport models. In: Hensher DA and Button K (eds) *Transport Geography and Spatial Systems*. Oxford: Elsevier, pp. 127–146.
Yang Q and Li X (2009) Agent-based micro-simulation of urban industrial spatial evolution. *Scientia Geographica Sinica* 29(4): 514–522 (in Chinese).
Zhang JQ and Chen YL (2011) Industrial distribution and clusters of urban office space in Beijing. *Acta Geographica Sinica* 66(10): 1299–1308 (in Chinese).
Zhao H, Yang KZ, Wei H, et al. (2013) Job-housing space restructuring and evolution of commuting patterns in Beijing metropolitan area. *Urban Planning* 37(8): 33–39 (in Chinese).
Zhou C and Ye C (2013) Progress on studies of urban spatial structure in China. *Progress in Geography* 32(7): 1030–1038 (in Chinese).
Zondag B, de Bok M, Geurs KT, et al. (2015) Accessibility modeling and evaluation: The TIGRIS XL land-use and transport interaction model for the Netherlands. *Computers, Environment and Urban Systems* 49: 115–125.

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